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A Comprehensive Study of Metaheuristic Performance on Job-Shop Scheduling Problems

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Abstract
The article presents an in-depth literature review on the performance of metaheuristics in operations scheduling problems and aims to evaluate the use of metaheuristics, concerning job-shop scheduling problems. In the first part, a literature review was conducted on the significance of operations scheduling and its different types, as well as metaheuristics and job-shop scheduling problems, providing historical context to the three topics. The methodology for the selection of the papers included in the bibliometric study is explained. Twenty articles from Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing and Tabu Search, addressing job-shop problems were selected. Then, various statistical analyses were conducted, such as the analysis of the evolution of results throughout the years and the performance comparison analysis between metaheuristics. Finally, a discussion about the results obtained is held, presenting the conclusions. The statistical analyses revealed that the performance of metaheuristics depends on multiple factors and that their evaluation should not be carried out in isolation. In terms of practical results, the analysis showed that Genetic Algorithms achieved the highest average makespan reduction, followed by Simulated Annealing, Particle Swarm Optimization, and Tabu Search. For example, GA consistently reduced makespan by more than 15% compared to industrial cases, while Tabu Search showed the least consistent performance across studies.

Keywords
Operations Scheduling, Metaheuristics, Job-Shop, Makespan, Optimal Result, Statistical Inference.

Introduction

Now more than ever, companies are faced with countless challenges that pressure them to meet the incessant demands of a continually growing market (Georgiadis et al., 2023). To remain competitive, they must continuously adapt to changing market demands to maintain their attractiveness. From an industrial perspective, industries have the role of providing quality products and services at appropriate prices (Graves, 1981). However, this also presents significant challenges. This is where operations scheduling comes in as a decision process that helps achieve these goals (Leung, 2004). The article aims to analyse and compare the performance of four metaheuristics (Genetic Algorithm, Particle Swarm Optimization, Tabu Search and Simulated Annealing) in job-shop scheduling problems.

In the second chapter, through an in-depth literature review, the role of operations scheduling in the industry is explored, some key aspects related to it, what metaheuristics are, their purpose, what job-shop scheduling problems are and the various characteristics they present. After that, in the third chapter the methodology behind the selection of articles is explained. Then, in the fourth chapter, various statistical analyses were conducted, and their respective results were presented. Finally, in the final chapter, the results from the statistical analyses were discussed and the final conclusions were presented.

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Literature review

Operations Scheduling

Effective operations scheduling makes all the difference in modern production processes, playing a crucial role in the service and manufacturing industries. Graves (1981) defines operations scheduling as the allocation of available production resources over time in a way that best fulfils a set of well-defined criteria. Baker (1974) defines it as the allocation of resources over time to carry out a set of activities. From these definitions it can be concluded that operations scheduling is a decision-making process that allocates resources to operations. Depending on the situation, these resources and activities can take different forms. Resources could be, for example, teachers at a school or mechanics at a repair shop, while activities could be the duties of teachers at a school or car repairs at a repair shop. Thus, activities can be seen as what is carried out by the resources (Leung, 2004).

The proper application of operations scheduling in an industry has numerous advantages such as reducing costs, increasing profits, reducing backlogs, among many others. However, it entails some highly complex problems that are difficult to solve, which leads many industries, without the appropriate resources to deal with them, to shy away from formally addressing the problem, despite its many benefits (Georgiadis et al., 2023).

The first studies related to operations scheduling date back to 1950, when several researchers from the fields of operations research, industrial engineering and management were faced with the problem of managing the various activities that took place in a workshop. Good operations scheduling algorithms could lead to a reduction in the costs of a manufacturing process, allowing the company to remain competitive. At the end of the 1960s, computer scientists also began to take part in the study of operations scheduling. Given that computer resources were scarce, efficient use of them could lead to a reduction in the costs involved in running computer programs (Guerreiro et al., 2023; Varela et al., 2022). These two factors together provided an economic reason for the further study of operations scheduling (Leung, 2004).

The characteristics of the industry are crucial in determining the type of Scheduling, and there are four main types:

- Static Scheduling – all activities are known and prepared from the start and do not change throughout the manufacturing process, regardless of whether new activities appear during the process. This type of scheduling is notorious for its lack of flexibility (Koskinen et al., 2020; Ouelhadj & Patrovic, 2009).
- Dynamic Scheduling – new activities can be added during the process, delivery dates can be changed, as well as the status of some of the machines. In this way, it is characterized by taking real-time events into account (Koskinen et al., 2020; Ouelhadj & Patrovic, 2009).
- Deterministic Scheduling – it is assumed that the parameters of the activities, such as processing times, are known a priori and precisely, which is typically the case in academic Scheduling Problems (Pinedo, 2008).
- Stochastic Scheduling – unlike Deterministic Scheduling, the parameters of the activities, such as processing times or delivery dates, are not known precisely, and these parameters are only known when they occur. This type of scheduling is closer to reality as it considers the strong component of uncertainty and randomness present in real production environments (Pinedo, 2008).

Metaheuristics

The human brain solves optimization problems on a daily basis using heuristics, for example, choosing the quickest route home after work or choosing a particular item to buy. Despite this, the scientific study of heuristics and metaheuristics is quite recent (Marti et al., 2024; Glover, 1986), and the term “metaheuristic” itself was only introduced in 1986 by (Glover (1986).

The term metaheuristic comes from the combination of two words “Meta” and “heuristic”. The Greek prefix “meta” means “beyond, at a higher level”, while the word “heuristic”, which derives from the Greek verb heuriskein, means “to find” or “to reach a goal”. Metaheuristics can therefore be seen as algorithms that combine heuristics into a more generalized structure (Kaveh, 2021; Bianchi et al., 2009).

Metaheuristics are approximate techniques that are widely used to solve Operation Scheduling Problems. They are algorithms that can be applied to solve these problems by reaching an approximate solution, using strategies to efficiently explore the space of solutions and avoid Local Optima. There are several metaheuristics that are used to solve complex Scheduling Problems, and their number continues to increase over the years. New metaheuristics provide more efficient ways of approaching traditional optimization problems and new ways of tackling unsolved problems (Torres-Jiménez & Pavón, 2014; Santos et al., 2016; Santos et al., 2022).

Early heuristic methods appeared between 1940–1960 and were popularized by Polya’s *How to Solve It* (Polya, 1945). In the 1960s, Rechenberg and Schwefel introduced Evolutionary Algorithms inspired by Darwin's theory of evolution (Auger, 2005; Darwin, 1859; Wu & Banzhaf, 1998). Holland (1975) later developed the first Evolutionary metaheuristic, the Genetic Algorithm (Katoch et al., 2021). In 1983, Kirkpatrick et al. (1983) introduced Simulated Annealing, inspired by the annealing process of solids (Kirkpatrick et al., 1983). In 1986, Glover (1986) both introduced the term "metaheuristic" and proposed Tabu Search, the first to incorporate memory (Glover, 1986). Between 1990 and 2000, swarm intelligence emerged with Ant Colony Optimization and Particle Swarm Optimization (Sörensen et al., 2018; Almufti, 2019). Since 2000, numerous new approaches such as Harmony Search, Artificial Bee Colony and Cuckoo Search have been proposed (Almufti, 2019).

This consistent growth reflects the need to solve increasingly complex problems where traditional methods are insufficient, with metaheuristics providing timely and practical solutions (Sequeiros et al., 2021).

Job-Shop Scheduling Problems

The Job-Shop Scheduling Problem is related to the fields of Industry, Economics and Management. This problem is part of a category of combinatorial optimization problems known as NP-hard Problems. Job-shop scheduling problems deal with a set of machines and jobs with several predetermined routes through the machines, in which the objective is to organize the scheduling of jobs in such a way as to minimize certain criteria such as makespan, maximum lateness and total tardiness.

These problems have various characteristics that allow them to be distinguished from one another, from their classification to the constraints present and their objective functions. With regard to their classification, job-shop scheduling problems can be considered deterministic, flexible, static, dynamic, among others. The three most common constraints are precedence, capacity, launch date and delivery date. Finally, the most common objective functions are minimizing makespan, maximum lateness and total tardiness. It is important to note that due to the attention and awareness that has been given to sustainable development and waste reduction in recent years, minimizing energy costs is an objective function that has been increasingly used (Albayrak & Önüt, 2024).

Over the last few decades, job-shop scheduling problems have been increasingly associated with metaheuristics, to the detriment of heuristics, because metaheuristics offer better solutions (Abdolrazzagh-Nezhad & Abdullah, 2017).

Methodology for the Selection of Articles

In this chapter, the most relevant and appropriate papers for the subject of this study were selected, which will later be used to analyse the performance of the different metaheuristics.

Thus, a search was made for articles in which Industrial Scheduling Problems of the Job-Shop type were solved using metaheuristics. Job-shop scheduling problems were chosen because of their high level of complexity, as well as the high frequency with which they are discussed by the scientific community. In addition, four metaheuristics were chosen in order to focus the research more on job-shop problems: the Genetic Algorithm, Particle Swarm Optimization, Tabu Search and Simulated Annealing.

The search for papers covered the period from 2010 to 2025, using the Web of Science and Google Scholar databases. It was decided to include older papers, published before 2010 to check for trends, where certain metaheuristics were used more frequently but, for whatever reason, lost popularity. Another reason was to see if there were any significant differences in the results from the use of metaheuristics over the years. Although the search window included 2025, no papers published in 2025 met the study's selection criteria and therefore none from 2025 were included in the analysis.

Table 1 summarises the aim search and selection parameters used in this study. Each article was screened for relevance by title and abstract, and then full texts were reviewed against the inclusion and exclusion criteria; ultimately 20 articles were selected and coded for the quantitative analyses reported in the Results section.

This study is limited to a systematic synthesis and statistical analysis of published results; original experiments were not conducted or included due to the scope of the work.

Genetic Algorithm

Twenty papers were selected in which GA was used to solve job-shop problems. GA is one of the most widely used metaheuristics for solving this type of problem, and there are more papers on GA than on the algorithms presented in the following subchapters. Because of this, most of the papers on GA are from recent years, between 2020 and 2025, which is not the case for the other metaheuristics.

After analysing the twenty papers selected, it was found that various types of GA are used, from simple GA to Improved GA and even Hybrid GA. In most of

Table 1
Summary of search & selection parameters

Databases searched	Web of Science; Google Scholar.
Search period	2010–2025.
Keywords	“Job-Shop Scheduling", “metaheuristic”, “Genetic Algorithm”, “Particle Swarm”, “Tabu Search”, “Simulated Annealing”.
Inclusion criteria	Papers addressing Job-Shop Scheduling solved using GA, PSO, TS or SA; peer-reviewed articles and conference papers; papers providing makespan or comparable performance metrics.
Exclusion criteria	Non-job-shop problems, papers without empirical results, or papers outside the defined search window (unless included as older papers for trend checks).
Number of Articles	Twenty articles per metaheuristic.
Selection process	Title/abstract screening followed by full-text review; relevant papers extracted and variables (e.g., makespan variation, proximity to optimal) coded for statistical analysis.

the papers reviewed, GA is compared to other metaheuristics or algorithms, or to an industrial case, in terms of makespan. The use of GA has consistently resulted in notable reductions in makespan. It should be noted that the most significant makespan reductions tend to occur in papers where the GA is compared to that of an industrial case or to that of a dispatching rule (Santos & Madureira, 2014), while the more modest are observed when GA is compared to other metaheuristics. This demonstrates the greater capacity that metaheuristics have in solving job-shop problems, which explains why, when they are compared to each other, the makespan reductions are less pronounced.

Particle Swarm Optimization

Twenty papers were selected in which PSO was used to solve job-shop problems. Although PSO is a well-known metaheuristic, it is not as widely used as GA in solving job-shop problems. Because of this, the papers collected on PSO cover a wider time window than those on GA, ranging from 2013 to 2024.

Although there are also papers in which PSO is compared to other metaheuristics, algorithms or industrial cases in terms of makespan, there are many more where the PSO does not prove to be the most effective solution when compared to other metaheuristics. This may be due to the fact that the PSO articles are older, the computational limitations at the time made it impossible to obtain lower makespan values, as it was not feasible to run a large number of iterations, due to processing constraints. The incremental improvements made to the PSO algorithm by the scientific community over the years also cannot be ignored, as they have contributed to its gradual enhancement and consequently, to improvements in makespan. Finally, another hypothesis that cannot be ruled out is that PSO may not be the most effective metaheuristic for the job-shop problems. Various types of PSO have been applied, including simple, improved and hybrid versions, though earlier studies did not fully exploit hybrid approaches.

In any case, it is also evident, in most PSO papers that, when it is used and compared to an industrial case or a dispatching rule, the reduction in makespan is quite significant, while when it is compared to other metaheuristics this reduction is more moderate.

Tabu Search

Twenty papers were selected in which TS was used to solve job-shop problems. Like PSO, TS is not as widely used as GA in job-shop problems, which is why the selected papers span a broader time frame, from 2010 to 2024.

As with PSO, TS also includes articles in which it does not provide the best solution. This may be due to the same factors identified for PSO: the older publications and the associated computational limitations; the incremental improvements introduced by the scientific community to the algorithm over time, contributing to gradual performance enhancements; or simply the possibility that TS is not the most suitable metaheuristic for solving job-shop problems. In addition, another important factor to mention is that due to past computational limitations, the Tabu List, a key parameter in TS performance, was smaller, which could result in higher makespan values. Today, thanks to technological advancements, larger Tabu List can be used, allowing for the achievement of lower makespan values. Both simple and hybrid TS have been used, though earlier studies did not fully exploit the advantages of hybrid approaches.

Simulated Annealing

Twenty papers were selected in which SA was used to solve job-shop problems. Among the four metaheuristics mentioned, SA has been used the least in job-shop problems, with the fewest articles available on the Web of Science database. The SA papers also span a wider time frame, from 2011 to 2025.

Both simple and hybrid SA have been applied in this type of problem. There are also papers in which SA does not yield the best solution.

Regarding the remaining papers, most show that when SA is compared to other metaheuristics, the reduction in makespan is modest, while when SA is compared to an industrial case or a dispatching rule, the reduction in makespan is more significant.

Statistical Analysis of the Results

In this point, inferential statistical tests were carried out to reach various conclusions about the performance of the four metaheuristics. IBM SPSS Statistics software was used, into which all the data from the papers was imported.

Before conducting the statistical tests, it was necessary to import the data into the SPSS software. To do so, all the variables required to fully characterize each article had to be created. Several variables were therefore defined, with particular emphasis on two variables that are essential to the statistical analyses:

- Makespan Variation (%) – a scalar variable indicating the percentage change in makespan. A negative value means that a reduction in makespan was achieved through the use of the respective metaheuristic, while a positive value indicates that the use of the given metaheuristic did not result in a reduction.
- Proximity of the metaheuristic Result to the Optimal Result (%) – a scalar variable that indicates how close the makespan result of a metaheuristic is to the optimal result, expressed as a percentage. The closer this value is to 0%, the closer the metaheuristic's result is to the optimal.

For each article, the reported performance values were manually coded into SPSS as numeric variables, ensuring consistent scaling across studies, with makespan always expressed as a percentage change relative to the baseline. In cases where certain indicators were not reported by a paper, the corresponding data field was left blank and treated as missing; SPSS handled these as system-missing values, and they were excluded pairwise from the relevant analyses.

Analysis of the Evolution of Results throughout the Years

The purpose of this analysis is to determine if there is a trend of improvement in the performance of the metaheuristics over time, from 2010 to 2025. The analysis was first carried out for the metaheuristics as a whole and then separately, for each of the four metaheuristics. The focus of this analysis was on the variation in makespan and proximity to the optimal result, and it involved scatter plots with trend lines as well as simple linear regressions.

The results obtained from this analysis are as follows:

- Metaheuristics as a whole – there is sufficient statistical evidence to conclude that, over the years, metaheuristics have achieved reductions in makespan. However, there is insufficient statistical evidence to conclude that the results of the metaheuristics have approached the optimum.
- Genetic Algorithm – there is evidence of reductions in makespan over the years, although the statistical evidence is not particularly strong. Similarly, there is insufficient statistical evidence to conclude that the results of the GA have approached the optimum.
- Particle Swarm Optimization – there is sufficient statistical evidence to conclude PSO has achieved makespan reductions. However, there is insufficient statistical evidence to conclude that the results of the PSO have approached the optimum.
- Tabu Search – there is evidence of reductions in makespan over the years, although the statistical evidence is not particularly strong. There is also insufficient statical evidence to conclude that the results of the TS have approached the optimum.
- Simulated Annealing – there is insufficient statistical evidence to conclude that SA has achieved reductions in makespan, and likewise insufficient evidence to conclude that its results have approached the optimum.

Performance Comparison Analysis between Metaheuristics

The purpose of this analysis is to assess which of the four metaheuristics tends to produce the best results. Therefore, the focus for this analysis were the makespan variation and proximity to the optimal result with the Kruskal–Wallis non-parametric statistical test being carried out.

The results of the Kruskal–Wallis test (P-Value $<$ 0.001) for the makespan variation are as follows: GA has the best average performance, followed by SA, PSO and, lastly, TS, which has the worst average performance. These results indicate that, on average, GA provided the highest reductions in makespan, while TS provided the smallest. The complete statistical results of this test are shown in Table 2.

The results of the Kruskal–Wallis test (P-Value 0.375) for the proximity to the optimal result are as follows: although TS presented the best average perfor-

Table 2
Makespan Variation by Metaheuristic

Group	Mean Rank
GA	50.07
PSO	79.37
TS	90.77
SA	72.56

Sig. (p) < 0.001

mance, followed by SA, PSO and GA, it is not possible to conclude, based on the statistical evidence that any of the four metaheuristics obtain results significantly closer to the optimum than the others. Detailed test statistics, including mean ranks and significance, are presented in Table 3.

Table 3
Proximity to Optimal Result by Metaheuristic

Group	Mean Rank
GA	17.67
PSO	16.70
TS	10.56
SA	13.28

Sig. (p) < 0.375

Analysis of the Variability of Results within each Metaheuristic

The purpose of this analysis is to assess the consistency of the results obtained by each metaheuristic and to conclude which of the four is the most consistent. Accordingly, the focus was, once again, the makespan variation and proximity to the optimal result. For each group of metaheuristics, the dispersion of the values for these two variables was quantified and was compared between the groups. The metaheuristics with the lowest variability are therefore the most consistent, even if they do not show the best average results.

Figures 1 and 2 show the results of the analysis in graphical form. The results showed that GA was the most consistent of the four metaheuristics, in both makespan variation and proximity to the optimal result. In contrast, TS proved to be the least consistent of the four metaheuristics, for both variables.

A qualitative interpretation helps contextualize these statistical findings. Many articles do not report optimal solutions, which limits the precision of analyses that rely on proximity-to-optimum as a metric. Authors also frequently prioritise tuning and demonstrating improvements of their own methods rather than performing rigorous comparisons to optima; choices such as using less-challenging instances or weak baselines (for example, dispatching rules or older industrial methods) can therefore artificially inflate observed makespan reductions. Regarding algorithmic features, GA's population-based search appears to increase its robustness: population sampling, crossover and mutation tend to average out poor initial choices and foster transferable implementation practices. By contrast, TS is typically trajectory-based and more sensitive to neighbourhood design, tabu-list strategy and parameter settings; combined with a larger presence in older, methodologically heterogeneous studies, this sensitivity likely explains its higher variability. Taken together, these points indicate that both average performance and stability (consistency across instances and implementations) should be considered when recommending metaheuristics for industrial Job-Shop problems.

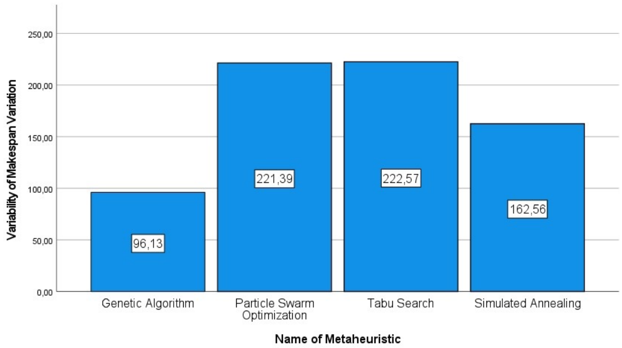

Fig. 1. Variability of Makespan Variation for each Metaheuristic

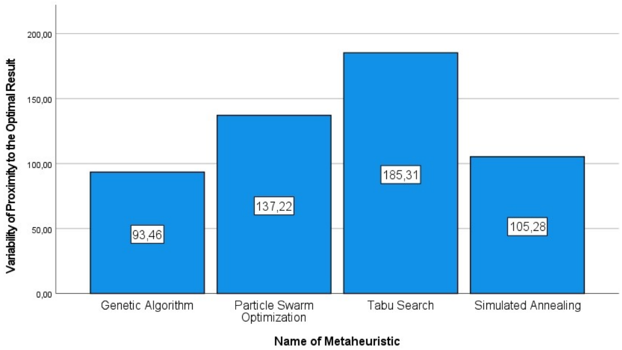

Fig. 2. Variability of Proximity to the Optimal Result for each Metaheuristic

Analysis of the Influence of Results Comparison Methods

The purpose of this analysis is to assess whether the performance of a given metaheuristic is better when compared to a given method. The comparison methods considered were other metaheuristics, industrial case and dispatching rule. For this analysis, the focus was the makespan variation.

The Kruskal–Wallis non-parametric statistical test was performed (P-Value < 0.001), and its results are as follows: the comparison to the dispatching rule has the best average performance, followed by the industrial case and, lastly, the other metaheuristics. These results indicate that, on average, the comparison of Metaheuristics with dispatching rules led to the highest reductions in makespan, while the comparison with other metaheuristics led to the smallest reductions in makespan. The full Kruskal–Wallis results by comparison method are reported in Table 4.

Table 4
Proximity to Optimal Result by Comparison Method

Group	Mean Rank
Other Metaheuristics	79.86
Industrial Case	27.63
Dispatching Rule	22.20
Other Metaheuristics	79.86

Sig. (p) < 0.001

Analysis by type of Metaheuristic: Hybrid and Non-Hybrid

The purpose of this analysis is to determine whether hybrid or non-hybrid metaheuristics tend to produce better results. Accordingly, for this analysis the focus was the makespan variation and the proximity to the optimal result, with the Mann–Whitney non-parametric statistical test.

The results of the Mann–Whitney test (P-Value 0.875) for the makespan variation are as follows: there are no statistically significant differences between the performance of hybrid and non-hybrid metaheuristics regarding makespan variation. Although the non-hybrid metaheuristics perform slightly better, this difference is not significant. The complete Mann–Whitney test results are provided in Table 5.

Table 5
Makespan Variation by Metaheuristic Type

Group	Mean Rank
Hybrid	73.50
Non-Hybrid	72.40

Sig. (p) < 0.875

The results of the Mann–Whitney test (P-Value 0.662) for the proximity to the optimal result are as follows: there are also no statistically significant differences between the performance of hybrid and non-hybrid metaheuristics in terms of proximity to the optimum. Although the hybrid metaheuristics perform slightly better, indicating results closer to the optimum, this difference is not significant. The full Mann–Whitney statistics are reported in Table 6.

Table 6
Proximity to Optimal Result by Metaheuristic Type

Group	Mean Rank
Hybrid	12.89
Non-Hybrid	14.21

Sig. (p) < 0.662

Conclusions

This paper analyses and compare the performance of four metaheuristics applied to job-shop scheduling problems.

First, an overview of operations scheduling was presented. Then the topic of metaheuristics was also addressed, focusing on their development and application. Finally, the topic of job-shop scheduling problems was discussed, mentioning the various characteristics that allow them to be distinguished from one another. Twenty papers from four metaheuristics were, then, selected and the data gathered from these papers was used to perform various statistical analyses, leading to several important conclusions.

The analysis of result trends over the years revealed that technological and methodological advances are not consistently reflected in performance metrics, raising concerns about the consistency and quality of approaches used in the literature. This reflects both the diversity of benchmark instances used and the fact that many studies emphasize relative improvements rather than consistent proximity to optimal solutions.

Comparing the performance of the different metaheuristics showed significant differences among algorithms, confirming that the choice of metaheuristic can greatly influence the solution. This underscores the importance of carefully selecting the most appropriate metaheuristic for each specific problem. GA emerged as the most consistent of the four, which may be explained by its population-based design, while TS showed greater variability, reflecting its higher parameter sensitivity and the methodological heterogeneity of older studies.

The analysis of result variability within each metaheuristic emphasized that consistency is crucial. Some metaheuristics demonstrated more robustness and predictability, which is particularly valuable in industrial contexts where the variability in results is a critical concern.

It was also shown that the comparison method substantially impacts the perceived effectiveness of the metaheuristic studied. Results were most impressive when metaheuristics were compared against dispatching rules, and more modest when compared with other metaheuristics, underscoring the decisive influence of the chosen baseline.

Finally, regarding the analysis by type of metaheuristic (hybrid and non-hybrid), no statistically significant differences were found. This outcome suggests two main hypotheses: either non-hybrid metaheuristics remain sufficiently competitive, or hybrid metaheuristics have yet to be fully exploited.

Overall, this study confirms that metaheuristic performance depends on multiple factors and that their evaluation should be comprehensive.

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